A Method for the Unified Representation of Multispectral Images with Different Number of Bands

Satoshi Nambu, Toshio Uchiyama*,*
Masahiro Yamaguchi,**, Hideaki Haneishi*,***, and Nagaaki Ohyama*,***
**Akasaka Natural Vision Research Center, TAO of Japan, Tokyo, Japan*
***Tokyo Institute of Technology, Kanagawa, Japan*
****Chiba University, Chiba, Japan*

Abstract

We propose a simple but useful method to represent multispectral images with different number of bands that are captured by different kind of multispectral cameras (MSC). It is necessary to represent them in a common space with sufficient accuracy of spectral information when consider-ing editing, such as blending and accurate color reproduce-tion under an arbitrary illuminant. To solve the problem, we utilize the idea of a virtual multispectral camera (VMSC) that transforms real multispectral images into virtual multispectral images. We design the sensitivities of the VMSC properly, and our unified representation can avoid some disadvantages of conventional PCA based methods. We experimentally demonstrate the color reproduction accuracy of our method by comparing with PCA based methods under modified versions of objects to be captured, and the numbers of both MSC and VMSC bands.

Introduction

The recent progress in multispectral image processing technologies has enabled us to reproduce the color of objects accurately under an arbitrary illuminant.[1-6] This advantage could make it possible to composite multispectral images without incongruity, even if those images are captured under different illuminations. We are intending to edit multispectral still images and video as it is done with conventional RGB images and video to create attractive video products with accurate color reproduction.

However, there exist many kinds of MSCs that produce multispectral images with different number of bands, and there is not yet a simple way of handling them together. Therefore, when considering editing, such as blending two or more video with different number of bands, we need a method to represent them in a common space. In addition, we want a simple representation of the edited result especially for real-time video processing at the moment of displaying.

Colorimetric representation, such as CIE XYZ-values, is well known as a common space, but it is unusable in the case when capturing and observing illuminations are different. We need to find out a method to represent sets of multispectral images with different number of bands, in a common space with sufficient accuracy of spectral information.

B. Hill[3] also pointed out the same problem in building color reproduction open system architectures. In which, assuming arbitrary numbers of bands for both input and output devices, input multispectral images with a certain number of bands have to be encoded in a generalized form for transportation to output devices.

One method to solve the problem is the expansion of spectral information estimated from each multispectral image, into orthonormal basis functions that are derived from principal component analysis (PCA) applied to a set of samples. With this method, all multispectral images are represented as coefficient images of the same set of basis functions.

One variation of this is called "compatible to the conventional tristimulus model" method in which the first three coefficients represent tristimulus values of a standard color space referred to a standard illuminant.[3,4] Another is weighted Karhunen-Loeve transform (WKLT) based on human visual sensitivities, and that is designed to minimize the color difference between the original and the reproduction.[5]

Those PCA based methods theoretically give one of the best results in a sense of minimizing square error. However, there exist some disadvantages of them. One is, since the basis functions depend on the set of samples, the best set of basis functions for one group might not be good enough for another group. We consider any kind of multispectral video as input. Therefore, it is impossible to get perfect basis functions of PCA for all. In addition, they may cause large differences in dynamic ranges of basis functions, and may cause unwanted negative pixel values for practical editing system software.

König et al. [6] reported significant simulation results by comparing color estimation accuracy using multispectral images from a VMSC using between 6 and 16 bands. The results suggested the possibility of keeping mean ΔE_{ab} error under 0.5 by using more than 10 bands. In this way, representation of spectral information as output images of a VMSC with such a small number of bands is reasonable for accurate color reproduction.

In this paper, we propose a simple but useful idea to define a VMSC with a certain number of bands (8 for example) that transforms real multispectral images with different number of bands into virtual multispectral images with the same number of bands for every input. We design our VMSC to have equal sensitivities for each band located at equal intervals over visible range, sensitivities are independent from input data. Our method can avoid the disadvantages of PCA based methods described above while keeping color reproduction accuracy.

We experimentally demonstrate how color reproduction accuracy changes when images with different number of bands are transformed to output images of the defined VMSC. In addition, some experimental results comparing our method with conventional PCA based methods are also shown.

Image model and Unified Representation of Multispectral Images

In this section, we describe a formulation of the image model that we used, and explain the unified representation of multispectral images with different number of bands.

Suppose that there exist multiple kinds of MSCs with different number of bands. Let $\mathbf{v}_i$ be a multispectral image captured by the i-th camera with N_i bands, and $\mathbf{r}$ be the spectral reflectance of the object represented in an M-dimensional space. Let $\mathbf{S}_i$ be an N_i x M matrix whose column vectors represent the sensitivity of the k-th band of the i-th camera, and $\mathbf{L}$ be an M x M diagonal matrix whose diagonal elements represent the spectral radiance of the capturing illuminant. We can then write expression for $\mathbf{v}_i$ in vector representation as follows,

$$\mathbf{v}_i = \mathbf{F}_i \mathbf{r} , \tag{1}$$

where $\mathbf{F}_i$ (=$\mathbf{S}_i\mathbf{L}$) is a linear system matrix with size of N_i x M. Note that each multispectral image $\mathbf{v}_i$ has a different number of bands N_i, while the spectral reflectance $\mathbf{r}$ is represented in the same M-dimensional space. Our problem is to find out a method to represent these $\mathbf{v}_i$ with different number of bands in a common space to handle them together. We will call this kind of representation that has only one form for all multispectral images as "unified representation".

It is known that we can get the estimated reflectance $\hat{\mathbf{r}}_i$ from each $\mathbf{v}_i$ by using Wiener estimation:

$$\hat{\mathbf{r}}_i = \mathbf{G}_i \mathbf{v}_i , \tag{2}$$

$$\mathbf{G}_i = \mathbf{R}_\mathbf{r} \mathbf{F}_i^T \left(\mathbf{F}_i \mathbf{R}_\mathbf{r} \mathbf{F}_i^T \right)^{-1} , \tag{3}$$

where $\mathbf{R}_\mathrm{r}$ is the correlation matrix of $\mathbf{r}$, which is related to *a priori* knowledge about the reflectance $\mathbf{r}$ of objects in the image for solving the inverse problem. $\mathbf{G}_i$ is a matrix with size of M x N_i.

Since $\hat{\mathbf{r}}_i$ in Eq. (2) is represented in the same dimensional space for all i, this could be considered as one of the unified representations we demand. However, $\hat{\mathbf{r}}_i$ use in general a so high dimensional space to approximate the continuous value of the spectral reflectance, that is not appropriate for practical applications in the sense of amounts of data. Therefore, we have to encode $\hat{\mathbf{r}}_i$ to reduce amounts of data. At that time, we need to concern about efficiency, accuracy and usefulness of this unified representation.

Virtual Multispectral Camera

Before explaining our idea to define a unified representation of multispectral images, we recall PCA based methods as a comparison.

By using a PCA method basically, the estimated spectral reflectance $\hat{\mathbf{r}}_i$ can be encoded into a coefficient image $\mathbf{x}_i$ in a lower dimensional space. This $\mathbf{x}_i$ theoretically gives one of the best representations in the sense of minimizing square error between the original $\hat{\mathbf{r}}_i$ and the one that is recalculated from $\mathbf{x}_i$.

However, since the basis functions of PCA depend on the set of samples, the best set of basis functions for one group might not be good enough for another group. Therefore, the optimal accuracy is only available for the images from the sample set. In addition, PCA based methods may cause large differences in dynamic ranges of basis functions, and may cause unwanted negative pixel values for practical editing system software. This might be a problem for usefulness.

Our method, on the other hand, can avoid these disadvantages of PCA based methods described above. The idea relies on the simulation results reported by König et al. [6], which suggested the reliable ability of a multispectral image from a VMSC with a relative number of bands to reproduce accurate color. A VMSC here means a virtual and unreal device with virtual spectral sensitivities, and that can transform spectral radiant distribution into a VMSC response. We utilize this VMSC to represent the estimated spectral reflectance $\hat{\mathbf{r}}_i$. We design this camera properly to have equal sensitivities for each band located at equal intervals over visible range of wavelength in order to be independent from input data, and not to produce negative pixel values. Further details are explained below.

First of all, using Eq. (1) and (2), we can transform a real multispectral image $\mathbf{v}_i$ with arbitrary number of bands or the estimated spectral reflectance $\hat{\mathbf{r}}_i$ to a virtual multispectral image $\tilde{\mathbf{v}}_i$ as,

$$\tilde{\mathbf{v}}_i = \mathbf{F}_{vmsc} \hat{\mathbf{r}}_i = \mathbf{F}_{vmsc} \mathbf{G}_i \mathbf{v}_i , \tag{4}$$

where $\mathbf{F}_{vmsc}$ is a matrix with size of N_{vmsc} x M that defines the properties of this transformation. Eq. (4) defines our VMSC. Since there are no differences between the form of $\tilde{\mathbf{v}}_i$ and $\mathbf{v}_i$, we can estimate spectral reflectance $\hat{\hat{\mathbf{r}}}_i$ again from $\tilde{\mathbf{v}}_i$ using Eq. (2) as,

$$\hat{\hat{\mathbf{r}}}_i = \mathbf{G}_{vmsc}\tilde{\mathbf{v}}_i \,, \tag{5}$$

where $\mathbf{G}_{vmsc}$ is a matrix that corresponds to $\mathbf{G}_i$ in Eq. (2), but that is independent from the linear system matrix $\mathbf{F}_i$. In addition, any applications for real multispectral images $\mathbf{v}_i$ can be applied to virtual multispectral images $\tilde{\mathbf{v}}_i$.

Now, let us think about the design of the matrix $\mathbf{F}_{vmsc}$, which is the key of our method. We should design $\mathbf{F}_{vmsc}$ properly in the sense of efficiency, accuracy and usefulness. We take a different approach from PCA based methods to avoid the explained disadvantages. In order to cover all kind of objects to be captured, we design our VMSC to be not optimized for particular sample data. To realize this, we used gaussian curves for definition of the k-th spectral sensitivity as,

$$F_{vmsc}(k,\lambda) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{\{\lambda-(\mu_0+\Delta\mu k)\}^2}{2\sigma^2}} \,, \tag{6}$$

where λ is wavelength and σ, μ_0, $\Delta\mu$ are constants, the capturing illuminant is represented by a unit matrix, this does not cause negative pixel values. An example of spectral sensitivities of an 8-band VMSC of Eq. (6) is shown in Fig. 1. Next, we confirm the color reproduction accuracy of our method through experiments.

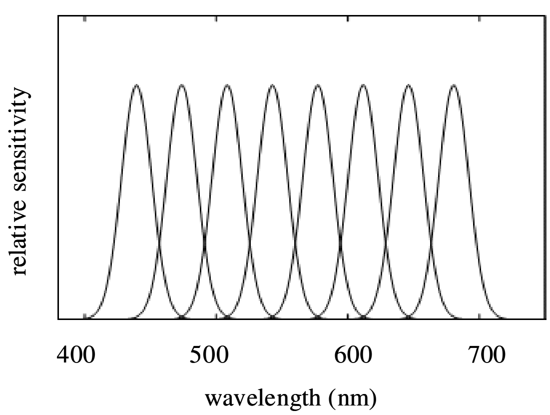

Figure 1. An example of spectral sensitivities of a VMSC

Experiments

We evaluated the color reproduction accuracy of our method under modified versions of objects to be captured, and the numbers of MSC bands and VMSC bands by making simulations. The object data we used for the simulations were sets of spectral reflectances of the Gretag Macbeth Color Checker measured by a spectroradiometer (Topcon SR-2), the natural objects measured by Vhrel, Gershon and Iwan,[7] and flowers, leaves, and paints from the SOCS (Standard Object Colour Spectra database for colour reproduction evaluation).[8] As real input devices, we used spectral sensitivities of real 3 and 6-band multispectral video cameras and a 16-band multispectral still camera.[1,2] The used illuminant for capturing was CIE D65, and the ones used for color reproduction were CIE D65, CIE A, CoolWhite, and TL84. We used Eq. (6) as definition of our VMSC with constant values σ, μ_0 and $\Delta\mu$ adjusted to cover the range between 380 nm to 780 nm at equal intervals. The numbers of VMSC bands were 4, 6, 8, and 10.

As seen in Eq. (1) to (5), there are three different types of reflectances. Which are A: the very original spectral reflectance $\mathbf{r}$ of objects, B: the spectral reflectance $\hat{\mathbf{r}}_i$ estimated from a real multispectral image, and C: the spectral reflectance $\hat{\hat{\mathbf{r}}}_i$ re-estimated from a virtual multispectral image of the VMSC whose input is B. We evaluated the differences of the re-estimated reflectance $\hat{\hat{\mathbf{r}}}_i$ against the original reflectance $\mathbf{r}$ to check the total system performance. Since there already exist estimation errors in the estimated reflectance $\hat{\mathbf{r}}_i$, differences of the re-estimated reflectance $\hat{\hat{\mathbf{r}}}_i$ against the estimated reflectance $\hat{\mathbf{r}}_i$ are also confirmed. For evaluation of the color reproduction accuracy from the re-estimated spectral reflectance, we computed the root mean square errors (RMSE) between the re-estimated and the estimated reflectances, and we also computed the ΔE_{ab} average color differences of the reproductions under the four illuminants.

We compared our method with two kinds of PCA based methods, which are a normal PCA method and WKLT.[5] The reflectance that is recalculated from the coefficient image of these PCA based methods corresponds to the re-estimated reflectance of our method. For ease of expression, we will use the term "re-estimate" for the both reflectances. Since we want to represent arbitrary multi-spectral images in a common space, the basis functions of the PCA should be also common. Therefore, we derived a set of basis functions from the estimated reflectances of the mixed set of all kind of input data groups. In addition, we also derived sets of basis functions from each individual input data group for reference. We indicated them by "mix" and "ind" respectively in Fig. 2 to 6.

Experiment 1

We used the 16-band real MSC and an 8-band VMSC or 8-dimensional PCA based methods. The number of VMSC bands was chosen by the assumption that the maximum and average color differences of ΔE_{ab} had to be under 2.0 and 0.5 respectively for both the Color Checker and the natural objects sets. We compared the color reproduction differences for various sets of objects. A comparison of average RMSEs for the re-estimated reflectance against the original reflectance is shown in Fig. 2, and a comparison of color differences is shown in Fig 3. In the figures, "MSC" means the estimated reflectance from the real MSC, that is shown for reference to see how much the re-estimated reflectance of each method lost color information from the estimated reflectance.

PCA(mix) and PCA(ind) made the best results for the average RMSEs in Fig. 2, but results were quite worse in color differences in Fig. 3. To get better results of color reproduction, human visual sensitivities have to be considered. As it was expected, WKLT(mix) and WKLT(ind) that are based on human visual sensitivities[5] made better results on measured color differences than PCAs. However, our method, which is not optimized for the sample set, gave the best result of all the methods except for the leaves set. One reason for this result is that we used *a priori* knowledge of smooth reflectance in Eq. (5), and the experimental data actually presented smooth reflectance.

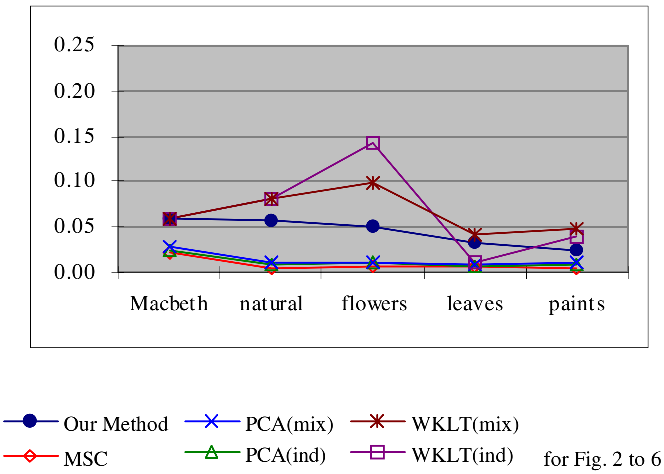

Figure 2. Average RMSEs for various object sets

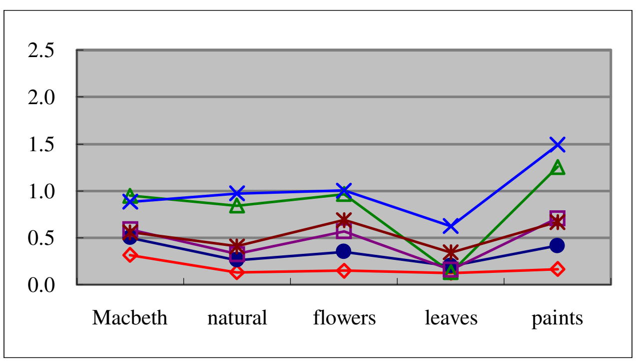

Figure 3. ΔE_{ab} average color differences for various object sets

Experiment 2

We used the 8-band VMSC, and the object sets of the Color Checker and the natural objects. We changed the number of input real MSC bands to see the effect on color differences. A comparison of the results about the computed average color differences of the re-estimated reflectance using natural objects against the original reflectance and the estimated reflectance respectively are shown in Fig. 4 and 5.

In both Fig. 4 and 5, the performance of our method was equal or better than the other four methods for almost all cases. We will briefly explain the reason why color differences of the recalculated reflectance against the estimated reflectance of PCA(ind) and WKLT(ind) for 3 and 6-band MSCs are zero in Fig. 5. Since the estimated reflectance $\hat{\mathbf{r}}_i$ represented in Eq. (2) has the same or less rank than the number of its MSC bands, it can be represented by higher dimensional PCA without error.

Experiment 3

We used the 16-band real MSC, and the object sets of Color Checker and the natural objects. We changed the number of bands of a VMSC or dimensions of a PCA to see the effect on color differences. A comparison of the results about the computed average color differences of the re-estimated reflectance against the original reflectance using natural objects is shown in Fig. 6.

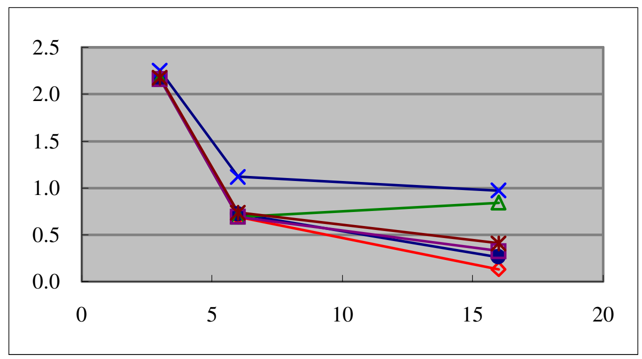

Figure 4. ΔE_{ab} average color differences vs. the number of MSC bands (against the original reflectance)

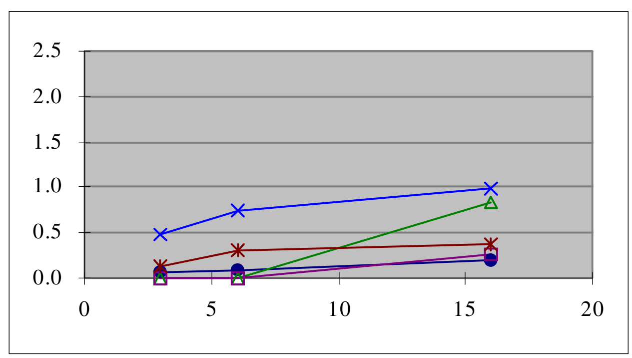

Figure 5. ΔE_{ab} average color differences vs. the number of MSC bands (against the estimated reflectance)

The performance of our method was equal or better than the other four methods in higher than 6-dimensional spaces, but it was worse than WKLT(mix) and WKLT(ind) in 4-dimensional space. This means that our method is effective in a higher dimensional space where the total color reproduction accuracy is high.

We have shown the color reproduction accuracy of our method through the experiments. According to the results, our method is not only acceptable but also produce better accuracy of color reproduction compared with conventional PCA based methods in almost all cases. This result suggests the remarkable effectiveness of our method for representing multispectral images with different number of bands in a unified common space. We consider that the reason for this result was the assumption of reflectance smoothness, but we will confirm it in future works.

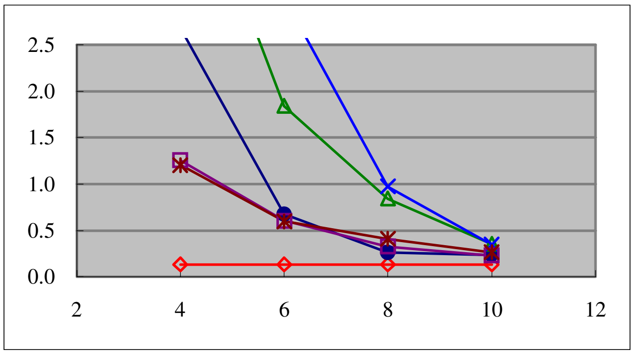

Figure 6. ΔE_{ab} average color differences vs. the number of VMSC bands or PCA dimensions

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Biography

Satoshi Nambu received the M. S. degree in Information Engineering from Nagoya University in 1998. In the same year, he joined NTT DATA Corp., worked at NTT Cyber Solutions Laboratories and Cyber Space Laboratories from 2000 to 2002, he is currently a researcher of Akasaka Natural Vision Research Center of Telecommunications Advancement Organization of Japan and a member of the Institute of Electronics, Information and Communication Engineering of Japan.